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MULTIOBJECTIVE DECISIONS AND THE FISHERY CONSERVATION AND MANAGEMENT ACT OF 1976

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The Fishery Conservation and Management Act (FCMA) of 1976 was passed by Congress both to prevent the decline of present fisheries and to encourage the development of under- or nonutilized fisheries. The intent of the FCMA is clear: Fisheries provide a multitude of benefits, such as economic, recreational, food production, etc., all of which are worthy objectives of management. At the same time the FCMA emphasizes the need to manage the fisheries in a manner that insures the continuation of the stocks and the benefits derived from the stocks. In order to carry out this law, eight regional management councils have been created, which have the responsibility to create management plans for each of the stocks under their jurisdiction.

In practice, the FCMA is being interpreted as requiring the regional councils to calculate a single number for each stock, the "optimum yield" (OY) for the stock. The criteria to calculate the "optimum yield" and to develop management measures are varied indeed in the FCMA. For example, OY is defined as:

> "...means the amount of fish--
>
> (A) which provides the greatest overall benefit to the Nation, with particular reference to food production and recreational opportunities; and
>
> (B) which is prescribed as such on the basis of the maximum sustained yield from such a fishery, as modified by any relevant economic, social, or ecological factors."

and management measures are required to:

"(5) Conservation and management measures shall, where practicable, promote efficiency in the utilization of fishery resources; except that no measure shall have economic allocation as its sole purpose.

(6) Conservation and management practices shall take into account and allow for variations among, and contingencies in, fisheries, fishery resources, and catches.

(7) Conservation and management measures shall, where practicable, minimize costs and avoid unnecessary duplication."

and OY again is defined as:

"The term 'optimum' is defined in this context...to mean the amount of fish from a fishery which if produced, will provide the greatest overall benefit to the Nation (especially in terms of food production and recreational opportunities) and which is prescribed for that fishery on the basis of the maximum yield sustainable therefrom (a biological measure) as modified by any relevant economic, social or ecological factor."

Some concern has arisen about how the regional concerns are to incorporate these myriad objectives into a management plan (see remarks prepared by Dr. James Crutchfield to Pacific Region Management Council[2]). Certainly the plans should not be whatever the councils want, but should be required to adhere to some kind of objective guidelines or methods in preparing and justifying the management plans.

Dr. Crutchfield proposes returning to "maximum sustained yield" (MSY) as "the reference point for council deliberations on OY. We would depart from it in a measured, justified, and explained way..." to include other criteria or objectives into the management plan. What concerns Dr. Crutchfield is that the FCMA requires the councils to develop management plans based on multiple, probably conflicting objectives, and there appears to be no "objective" method of determining plans in such situations. The purpose of this paper is twofold. First, a consistent terminology and methodology is presented, which allows us to define what we mean by a policy, a "good" policy, and an "optimal" policy. This terminology and methodology can be used in either the single or multiple goal setting. Furthermore, a policy as we define it, takes into account variations in stock size, catch, environmental factors, etc.

Second, using the framework provided in the previous section, we see to what extent we can define sustained yield for a multiobjective problem, and consider what approach Dr. Crutchfield has suggested in his comments. We show that there are several other approaches available which appear to us to be more suited to the responsibilities of the regional councils. This paper is the descriptive framework of a paper to be presented at the Joint ORSA-TIMS National meeting (San Francisco, May 1977) where some of the mathematical and algorithmic aspects of "good" policies for managing fisheries will be discussed.

I. States, Actions, and Policies

In order to be able to clearly talk about sustained yield and multiobjective decisionmaking, we must develop precise definitions of what we mean by policies, decisions and "optimal" policies. Our definitions are borrowed from the dynamic programming literature (see Denardo[5]). Other definitions are possible, but these particular definitions have a consistency that can be used in mathematical formulations of the problems.

The first part of a decision problem is to decide the length of the planning horizon T, that is, the number of periods into the future that will be included in our assessment of how well we are doing. Next, we must have a set of states that describe the system at some point in time. In a fisheries context, the state might be the stock size at the beginning of the period, or the size of each age class, etc. Associated with each state are a set of possible actions or decisions. The decision might be the amount of fishing effort this period, or the age-specific harvest rate, etc.

In each period, given the state and the decision, we must have a transition function which tells us the state at the start of the next period. The transition function need not be deterministic: that is it may only describe with what probability we expect to reach a given state in the next period, knowing our state and decision this period.

We can now define what we mean by a <u>policy</u> (we restrict ourselves to "feasible" policies, that is ones that are attainable given the dynamics and constraints of the system). A policy is a contingency plan that describes, for each possible state in each and every period in the planning horizon, what action to take in that period. The reason for such a general definition is that our transition function may not be deterministic. We do not know what state we will be in in any period in the future, so we must develop a plan which considers all possible states.

Let us assume that we have some means of comparing the time streams of period by period returns from every policy. For example, we might assume that in each period t there is a return function $G_t(x, y)$ which describes the return for each state x and decision y. In this case, we might want to:

$$\text{maximize } E \sum_{t=1}^{r} G_t(x_t, y_t)$$

where E is the expectation (average) operator. Or else we may have developed a utility function to compare the time streams, as in Keeney[6]. In either case, by an <u>optimal policy</u> we mean a policy that produces the greatest return given the desired method of comparison.

A complete discussion of optimal policies for renewable resources can be found in [1, 8, 9, 10, 13]. As an example, assume that x_t is the stock size at the beginning of period t, y_t is the stock size at the end of period t, that there is a return from harvest in period t of $\alpha^{t-1}p_t(x_t - y_t)$, $0 < \alpha \leq 1$ (that is linear benefits from catch, discounted by a rate α) and that the population dynamics are given by $x_{t+1} = s[y_t, D_t]$ where D_t is a random variable reflecting the influence of the environment, inaccurate measuring or imprecise modeling. Then in each period t, an optimal policy is described by a base stock size x_t^o (see Table 1).

Table 1.--Optimal policy for linear returns.

Population size at beginning of period	Optimal catch size during period	Optimal population size at end of period
$x_t > x_t^o$	$x_t - x_t^o$	x_t^o
$x_t \leq x_t^o$	0	x_t

If the initial population size is greater than the base stock size, then it is optimal to harvest to the base stock size x_t^o. Otherwise, it is optimal not to harvest. Notice that the policy does not call either for sustained catch or for sustained effort. An optimal policy is state specific, and the amount the optimal catch will vary will depend on the amount of fluctuation in the "production" (transition) function.

The main point of this example is to clarify what we mean by "optimal," "policy," and decisions, and to show why uncertainty makes it necessary to use such definitions.

II. Multiobjective Decisions

Multiobjective decisionmaking has been an active area of recent study in the field of operations research (see the extensive bibliography published in Zeleny[17]*). The main interest of study is decisionmaking when the multiple goals are conflicting in their aims. In what sense is it possible to talk about "optimal" or "good" policies. For clarity of exposition, we consider at first only the static problem, that is our planning horizon consists of a single period. Assume for each state x (possibly a vector) there are j possible decisions or actions, given by the vector $y = (y_1 \ldots, y_j)$. In a fisheries context, the j actions might be the amount of fishing effort allowed different sectors of the fishery. Given the state x, and the decision y, we assume there are k return functions $j \leq k$, $G^1(x, y)$, $G^2(x, y) \ldots$, $G^k(x, y)$ each of which independently measures the benefit in some sense, from observing state x and making the decision y. For example, G^1 might represent the economic benefit, G^2 might represent food or protein production, G^3 might represent benefits to recreational fishermen. Then, by an "optimal" policy for state x, $y^*(x)$, we mean a realizable decision $y^*(x)$, such that:

$$G^i(x, y^*(x)) \geq G^i(x, y)$$

$$\text{for } i = 1, \ldots, k$$

$$\text{and for all attainable } y.$$

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*In this section, references to authors mean the cited works in this bibliography, unless a specific alternate reference is given.

That is, the decision $y^*(x)$, out of all possible decisions, is simultaneously optimal in each and every objective. For conflicting objectives, rarely does such a policy exist, and real world experience confirms this observation. For example, in the California anchovy fishery, policies that are economically optimal for the reduction fishery overfish in terms of maintaining anchovy stocks as food for recreational fish.

While we may not be able to talk about "optimal" policies in the multiobjective case, we can define "good" policies. However, it is worth noting that a "good" policy will depend on both the objectives involved and on the particular definition of "good."

Multiobjective decisionmaking has taken two basic approaches: Prior weighting of the objectives and posterior weighting of the objectives. In the first category are methods such as determining utility functions, goal programming, and just plain assigning weights. In the latter category are programming techniques to determine "nondominated," "noninferior," "efficient," or "weakly-maximal" decisions.

Several examples of using utility functions in managing fisheries have appeared recently (see Tomlinson, Verlinsky, or Keeney[6]). A utility function reduces the multiobjective problem to a single dimension. That is, each possible combination of the k objective functions is reduced to a single number that represents our overall preference for that particular mix of returns. In practice, carefully chosen pairwise comparisons of returns are showed to the "decisionmaker," who chooses one as "preferred." Repeating this process can eventually lead to the determination of a utility function. (For a complete discussion of utility theory, see von Neumann and Morgenstein[16]; Luce and Raiffa[7]; Fishburn or Keeney among others.)

One type of utility function is a weighting of the k-objectives. That is, for each state x and decision y, the total return is $J = \sum_{i=1}^{k} \lambda^i G^i(x, y)$ such that $\sum_{i=1}^{k} \lambda^i = 1$. The weights are determined beforehand, and we are left with a straight optimization problem. One widely known version of this is "goal programming" (see Charnes and Cooper, or Lee). In "goal programming," rather than an objective function, there are k fixed goals, which are ranked in order of importance. The k goals are then assigned incommensurable weights, that is a higher goal is so weighted that if feasible, it will always be approached before a lower ranked goal. The problem then is to minimize the total weighted absolute deviation from the goals, which can be solved by linear programming codes. What makes goal programming nontrivial is that constraints on the problem often bring lower ranked goals into the final solution ahead of a higher ranked goal.

A priori weightings have the strong advantage that computational methods to calculate optimal policies for these problems are available. However, it is our feeling that for most problems arising from the FCMA that this is not the approach to take. First, it is not at all clear whose utility function should be determined in managing a fishery. The regional management council? The executive director of the council? In a sense, this line of reasoning puts the council ahead of the law. Dr. Crutchfield's remarks cited in the introduction are relevant here--the councils are not set up to do whatever they want. Moreover, we have little experience at multi-objective management for fisheries, and it is our feeling that few people will have a good intuitive feel for what a stated preference means in terms of its effects on each segment of the fishery. However, there are certain cases where these techniques seem most applicable. The tuna-porpoise problem seems to us to be a good example. Unless the Marine Mammal Protection Act is severely modified, the law has made the decision that goals concerning maintaining porpoise are more important than economic goals of the tuna industry. In fact, as now interpreted by the courts, the goal of maintaining the porpoise is incommensurably more important. Thus, we have a goal programming like problem. If Senator Hayakawa's bill passes the senate, the weighting will be reversed, and again we are reduced to an optimization problem that is relatively simple. Of course we have our own preferences on this particular problem,but our point here is to demonstrate the applicability and limitation of our procedures.

The "posterior" methods do not produce a single solution. Rather they are procedures that eliminate policies so that what is left are a set of policies none of which can be said to be "better" than any of the other policies in the set. For example, Yu has developed the concept of a "nondominated" solution (see Yu; Yu and

Zeleny; Leitmann and Yu; Bergstresser, Charnes, and Yu). Let $G^{(x, y)}$ represent the vector of k objective function $G^1(x, y), \ldots, G^k(x, y)$. Let $G(x, y^*)$ and $G(x, y)$ be two alternate values of the vector. Associated with each vector of returns G is a "domination structure" D(G), that is $G(x, y) \neq G(x, y^*)$ and $G(x, y)$ is contained in the set defined by $G(x, y^*) + D(G(x, y^*))$ then $G(x, y)$ is said to be dominated by $G(x, y^*)$. A particular example of a domination structure is given by:

$$D(G) = \{(d_1, d_2, \ldots, d_k) \mid d_1, d_2, \ldots, d_k \leq 0\}$$

with strict inequality holding for one component. This domination set states that an increase in the value of any objective function is always preferred. This is also the domination structure which defines a "Pareto optimal" or "efficient" point. That is $G(x, y^*)$ is "Pareto optimal" if there exists no attainable y such that

$$G^i(x, y) \geq G^i(x, y^*) \quad i = 1, \ldots, k$$

with one of the k inequalities being a strict inequality. For example, consider these four vectors of "returns":

$$(2, 4, 7, 1); (8, 5, 9, 1); (3, 5, 2, 2); (4, 7, 7, 6)$$

The second and fourth vectors are Pareto optimal. To see this, note:

$$(8, 5, 9, 1) \geq (3, 5, 2, 2)$$

$$(8, 5, 9, 1) \geq (2, 4, 7, 1)$$

$$(4, 7, 7, 6) \geq (3, 5, 2, 2)$$

$$(4, 7, 7, 6) \geq (2, 4, 7, 1)$$

However, there is no simple ordering between (8, 5, 9, 1) and (4, 7, 7, 6). Thus each is in some sense a "good" policy (or returns from a "good" policy).

Several authors have shown that in many instances, particularly if the objective functions are linear or concave and nondecreasing, then each efficient point is equivalent to the optimal point for some linear combination of the k-objectives, that is for some λ^i, $i = 1, \ldots, k$, $\sum_{i=1}^{k} \lambda^i = 1$ and with $J = \sum_{i=1}^{k} \lambda^i G^i(x, y)$. Each efficient point represents some weighting of the k objectives, though not all weightings are equivalent to an efficient point. This is why we have termed these procedures "posterior" procedures, in that the weighting(s) are found rather than determined beforehand. These procedures have the advantage of presenting the council with a vaiety of alternatives, each of which represents a weighting of the objectives, and each of which is a "good" policy in some well defined sense of the word. These procedures have the disadvantage that computationally they are more difficult, and also because it is possible to have a problem that has a multitude of such "good" policies, so that little has been gained by the effort.

A final solution concept to the multiobjective decision problem is to allocate to each element y^j of the decision vector y that which it would obtain at a "competitive equilibrium." By a competitive equilibrium, we mean a point where each "player" simultaneously maximizes its return against a fixed policy of all the other "players." Thus at a competitive equilibrium, each player is maximizing its return against the other players best strategy. If any player deviates from that point, they will decrease their own return (see Nash[11]; DeBreu [3]; Luce and Raiffa[7]; or Owen[12] for a discussion of game theoretic solution concepts). As a solution concept, competitive equilibriums or other game theoretic "solutions" leave the government, or government agency, such as the regional councils, the role of arbiter or mediator, which is a more passive role that it would seem is the intent of the FCMM. However, there is a large and growing literature on applications of game theory that lend this some appeal.

One of the main advantages of the techniques or concepts we have discussed is that they all, except perhaps for goal programming, readily extend to include multiperiod, dynamic decision problems. Now, instead of comparing objective functions from one period, there is a period by period time stream of vectors of objective functions or returns. Utility functions usually are discussed in the dynamic context, and the references cited earlier provide a good base. Leitmann and Yu extend the concept of nondominated solutions to dynamic, continuous time, deterministic models. Sobel[15] discusses Pareto optimal and competitive equilibrium solutions to discrete time, stochastic problems, with either ordinal or cardinal preferences (see also Denardo[4] and Sobel[14]). Computational experience with such problems is very limited, but at least it provides a consistent framework to begin to set guidelines and to evaluate our decisions when there are multiple, conflicting objectives.

III. Maximum Sustained Yield (MSY) and the FCMA

In this section we return and evaluate Dr. Crutchfield's proposal cited in the introduction, but using the techniques and concepts we have developed. Though we do have some reservations about Dr. Crutchfield's comments, our main purpose is to demonstrate that even when we are not calculating "solutions" to specific problems, our techniques are still a useful and potent tool.

One criterion we require from all suggestions for guidelines to the councils is that all the terms be precisely defined. By precisely, we mean it is clear how to obtain a number (or numbers) from the terms, since the FCMA requires that we manage effort and catch and stock sizes. Examples of imprecise terms are statements such as "it is desired to insure the future stock sizes" or that the yield "on the average" be maintained. The problem with the first term is that if we believe stocks fluctuate in ways we cannot control completely, when we say "insure the future stock sizes" do we mean no lower than a certain size?, or within a range of sizes? Do we mean, with probability one, the stock, in all future periods, does not leave this range, or do we mean that we minimize the probability of future stock sizes departing from this range? As an example, there is some feeling that the California anchovy and sardine have natural cycles that are independent of harvesting effort. If this is assumed to be true, what does it mean to insure the future stock sizes of the anchovy—there is no policy that insure this.

The second term is vague because there are too many ways of taking a long-term average, particularly if we are averaging over a stochastically fluctuating phenomena. We will see this more clearly in a moment.

Dr. Crutchfield has advocated a guideline of returning to MSY and deviating from it in a measured, justified way. In our terminology, Dr. Crutchfield recommends a prior weighting of the goals, with MSY being given the highest weight, almost an incommensurably high weight. Thus, rather than establishing guidelines for the councils to consider in determining policy, Dr. Crutchfield has suggested the form the councils objective function should take. Presumably the rationale is that MSY is in some sense equivalent to "maintaining the stock," and it is this underlying goal that is being given the highest weight by Dr. Crutchfield. However, it is not clear that MSY is equivalent in any sense to "maintaining the stock," nor is it clear that an optimization problem which desires to minimize the probability that the stock size drops below a certain prescribed level will produce a sustained yield policy as its solution (in fact, results in [8] suggest the opposite).

To see this more clearly, let us examine what we mean by MSY. MSY is usually defined in the context of single species, pooled age class, deterministic models. The sustained yield at any population size is the net growth in the population. The MSY is the maximum growth possible. Suppose however, growth fluctuates, so that it is possible that if we harvest the expected growth, we may in fact reduce the population below the initial population size. Repeated instances of this certainly will not maintain the stock size. Suppose instead we assume we want to maximize the expected long run (time)-averaged growth. It follows from [8] that a constant effort or sustained yield policy is again not optimal, and in fact has the same detrimental possibilities mentioned earlier.

Suppose we are trying to balance biological goals with recreational goals. In this instance, age-specific models are probably the most useful. What does MSY mean here? Does it require a constant age specific profile, a constant total number, a periodic return to a specific profile, or what? Consider especially the difficulty if we assume there is density dependent recruitment and fluctuating rates.

There are no easy solutions to the problems that the regional councils face. However, we can require that all suggestions and policies to and from the councils meet certain guidelines. The type of guidelines we suggest is that first, all terms be defined in a way that makes clear how they are to be measured. Second, when a policy is said to be "optimal," or "good," that the sense of these words be clearly defined, that the different objectives be clearly stated, that the weightings to each objective that will occur following this policy be clearly discussed, and that the reason alternatives were rejected be mentioned. We have presented in this paper numerous definitions of "good" and "optimal," which can be calculated from data. These do not exhaust the possibilities, but certainly suggest that we can clearly define and objectively evaluate a multiobjective decision problem.

Finally, the emphasis on a single number, "optimum yield," should be dropped, replaced instead with reasons why a particular allocation of catch, effort, entry, etc., was chosen, what this means in terms of present and potential effects, and also what it implies for present and potential yield.

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